Forecasting the behavior of the aFRR energy market

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Introduction

The intermittent nature of **renewable energy sources**, such as wind and solar, disrupts the **electricity grid stability** and supply-demand balance. The **Automatic Frequency Restoration Reserve (aFRR)** is a grid balancing mechanism that matches the electricity consumption and production to maintain the grid frequency at **50 Hz**. However, predicting aFRR price fluctuations is complex due to market volatility and the influence of external factors. This project aims to develop a **machine learning model** to forecast aFRR energy down and up prices for the next **48 hours**. The goal is to enhance grid stability, reduce electricity costs, and optimize the profitability of market participants in the evolving energy landscape.

Dataset

Timeframe	June 20 - Dec 1, 2024, Post-PICASSO
Original Records	15,936 15-minute data
Aggregated Records	3,937 hourly data
Missing Data	3.89 %, both Down and Up missing
Features	13 Fingrid and weather features

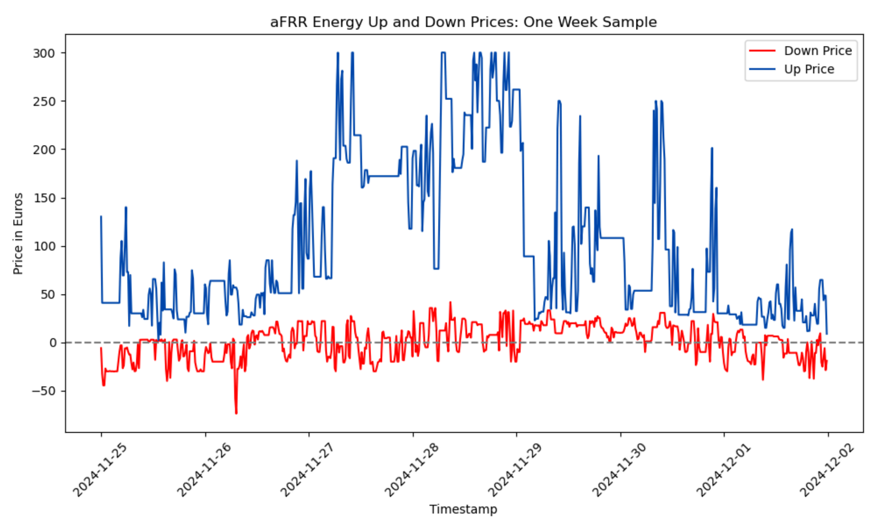

Figure 1. One week sample of aFRR energy prices.

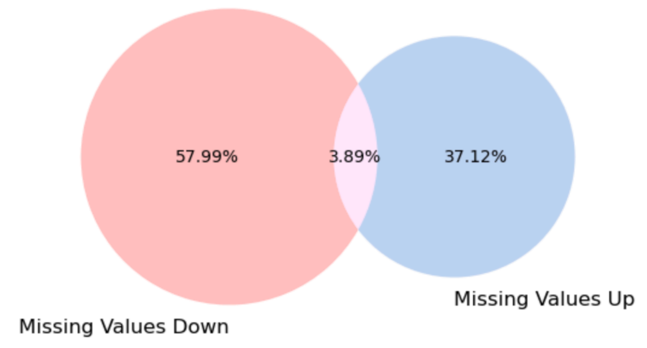

Figure 2. Missing values of aFRR energy prices.

Methodology

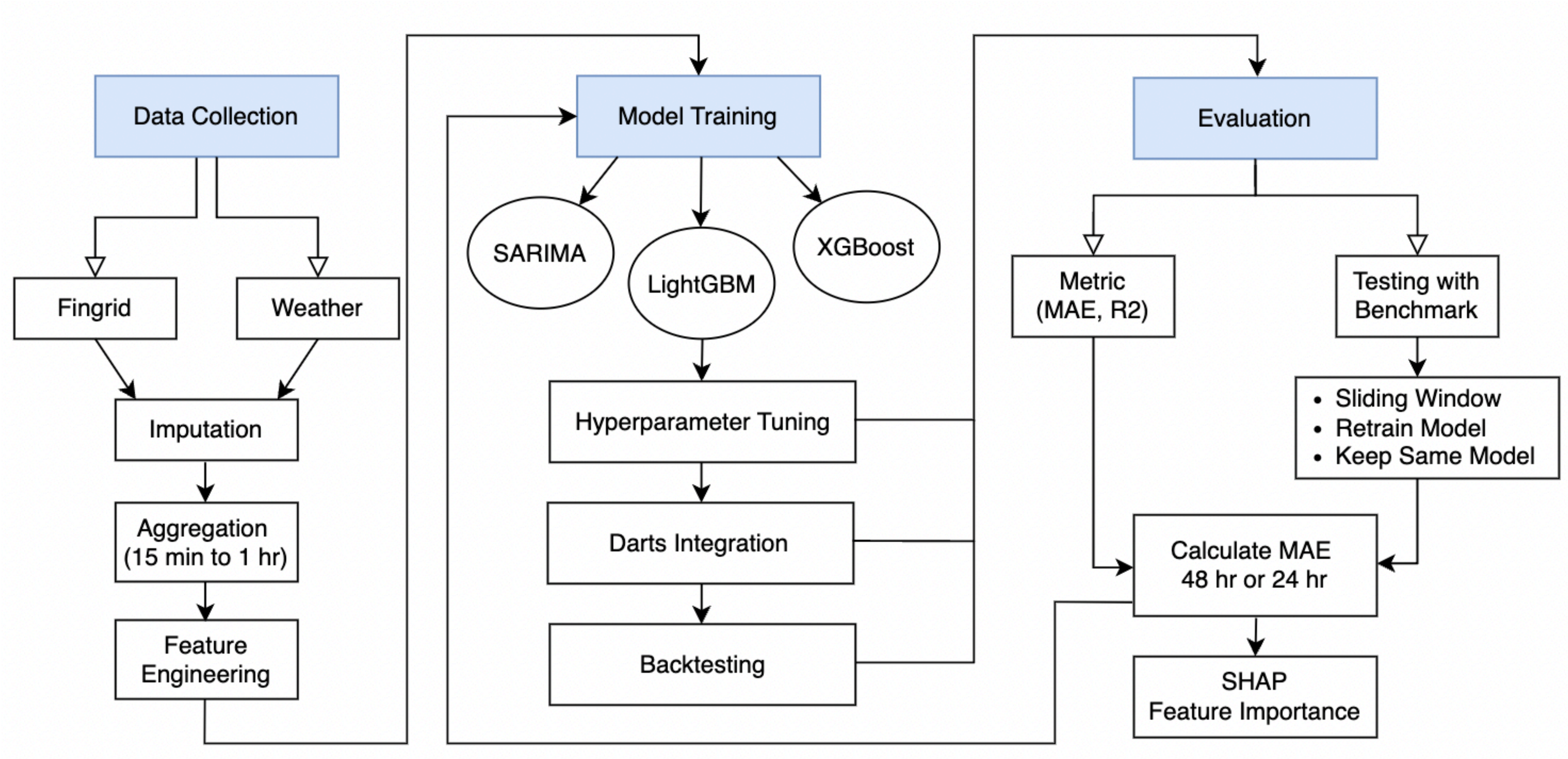

Figure 3: aFRR energy market price forecasting pipeline

The overall pipeline is illustrated in Figure 3:

- **Model Development** – Trained multiple models (SARIMA, ARIMA, TImesFM, Prophet, XGBoost, LightGBM) on Finnish hourly data (aggregated from 15-min intervals). LightGBM performed best, later enhanced with weather-based feature engineering.
- **Optimization & Backtesting** – Fine-tuned LightGBM with Optuna, validated with TimeSeriesSplit and integrated Darts.LightGBM for past and future covariates and backtesting.
- **Benchmarking** – Compared predictions with Elisa benchmark data (benchmark vs. true values, predicted vs. true values).
- **Sliding Window Testing** – Evaluated two strategies: (i) Retraining a new model per 60/90-day window and (ii) Fine-tuning an existing model incrementally.

Preliminary Results

After testing multiple models, the baseline **LightGBM** model performed best and was selected as the foundation. Initially, it used market prices and weather features, but since **market price features** will be unavailable at prediction time, we expanded the feature set with **time-based**, **weather-based**, and **lagged weather** features to ensure the model had sufficient information. Later, we incorporated **Darts.LightGBM** to take advantage of both **past** and **future covariates**, along with **backtesting** and **TimeSeriesSplit** for validation.

Table 1: Comparison of Base LightGBM and Darts.LightGBM Performance Metrics.

Model	Target	MAE	R^2 score
LightGBM	Down	8.78	0.69
	Up	23.95	0.62
Darts.LightGBM	Down	9.28	0.36
	Up	36.56	0.29

When tested and evaluated using a sliding training window approach, the LightGBM model with weather covariates outperforms benchmark results in forecasting both up and down energy prices.

Table 2: Sliding window testing comparison between predicted and benchmark values.

Metric	True vs Predicted	True vs Benchmark
Down MAE	13.182	19.261
Up MAE	41.675	60.138

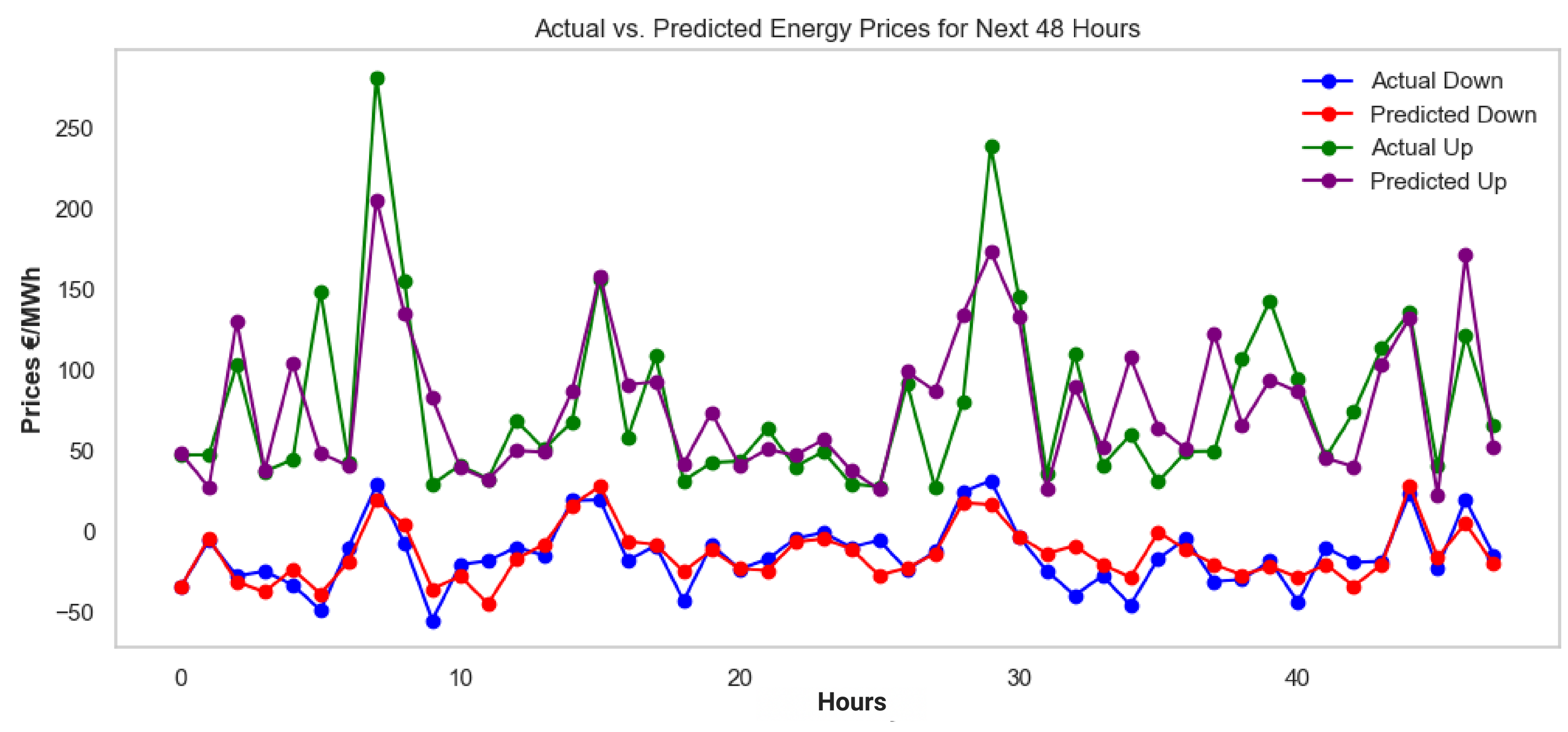

Figure 4. Actual vs Predicted energy prices comparison for base LightGBM.

Future work

Our work continues with Darts.LightGBM hyperparameter tuning and sliding window testing to refine and thoroughly evaluate the model. Future efforts will focus on exploring **advanced deep learning architectures**, such as **LSTMs** and **RNNs**, and **transfer learning** to improve forecasting accuracy.

Conclusion

Our project improves energy price forecasting by using machine learning to increase prediction accuracy and adaptability in volatile energy markets. We addressed the challenge of **limited real-time market data**, ensuring the model is practical for real-world applications. By enhancing forecasting precision, this approach is especially beneficial for the **Nordic market**, where renewable energy reliance leads to significant fluctuations in consumption and demand.

References

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